REGRESSIONS

Carlos J. Costa

Learning Goals

- Know concept of regression
- Distinguish between main algorithms
- Apply algorithms by using python libraries

Regression

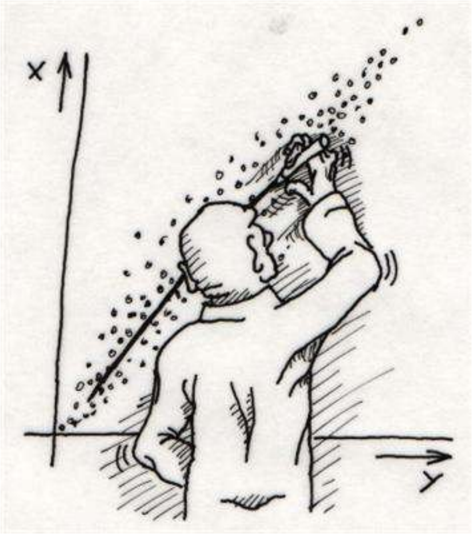
- Statistical processes for estimating the relationships among variables.
- Dependent variable, outcome variable, target
- Independent variables, predictor, covariates, or features

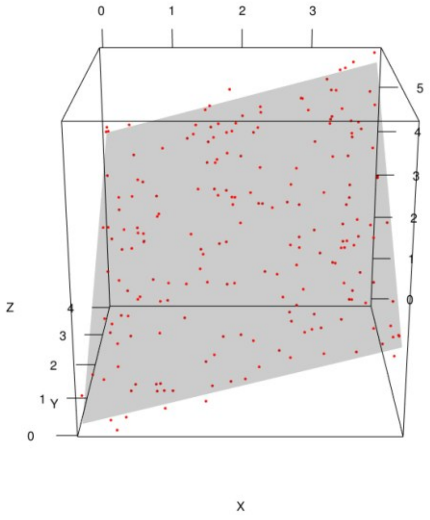
Regression

- simple regression/multivariate regression

$$Y_i = \beta_0 + \beta_1 X_i + e_i$$

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + e_i.$$



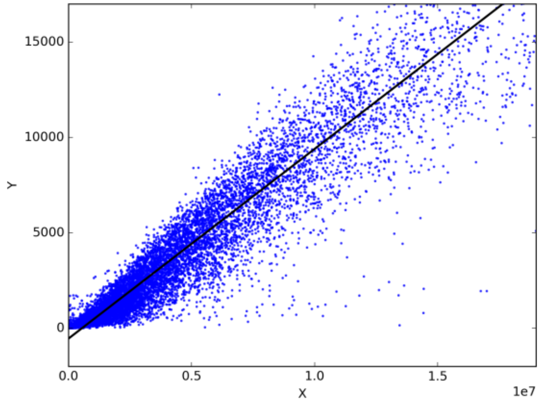


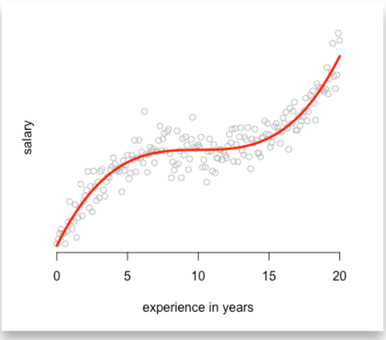
Regression

- Linear/non-linear

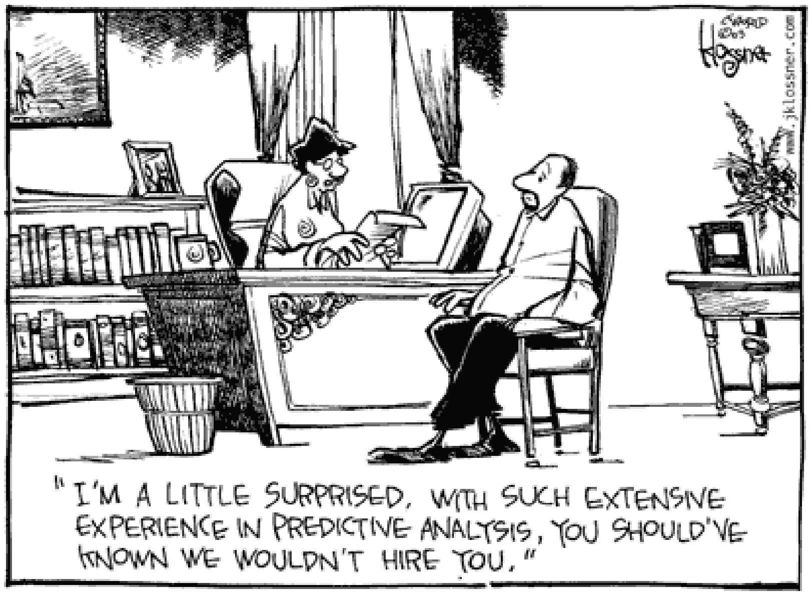
$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i, \quad i = 1, \ldots, n.$$

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \varepsilon_i, \ i = 1, \ldots, n.$$

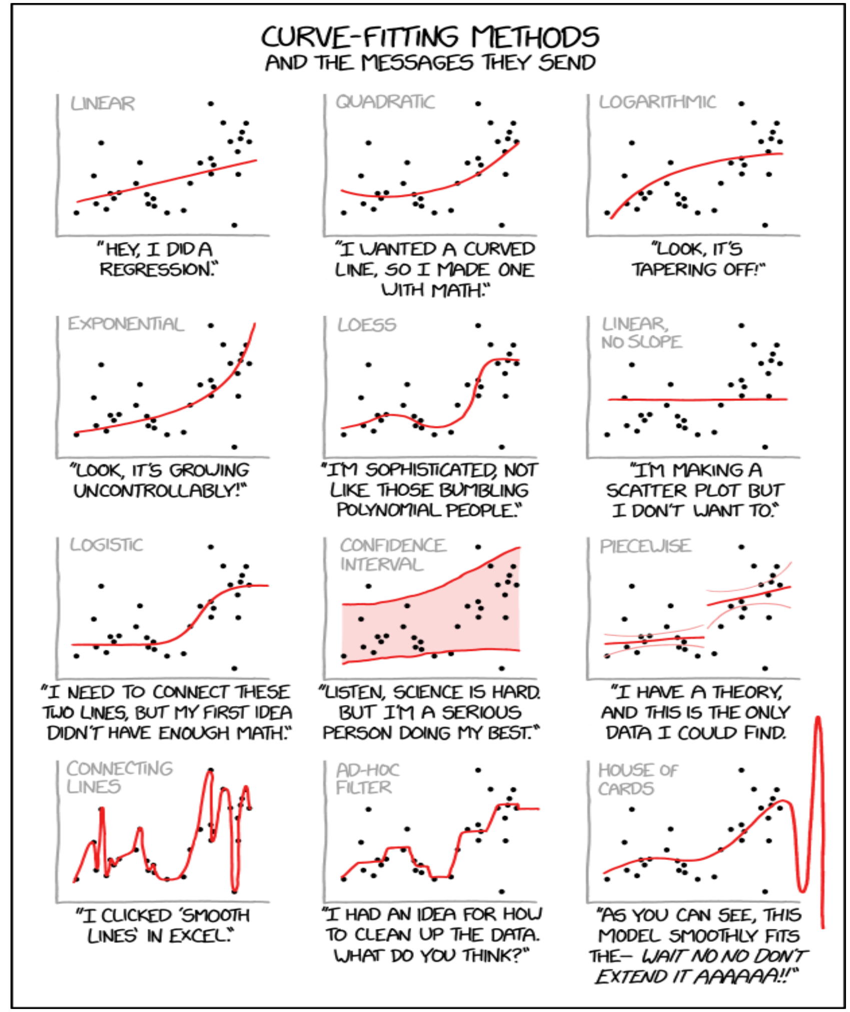




Regression



www.jklossner.com
"I'M A LITTLE SURPRISED, WITH SUCH EXTENSIVE EXPERIENCE IN PREDICTIVE ANALYSIS, YOU SHOULD'VE KNOWN WE WOULDN'T HIRE YOU."



CURVE-FITTING METHODS
AND THE MESSAGES THEY SEND
LINEAR
"HEY, I DID A REGRESSION."
QUADRATIC
"I WANTED A CURVED LINE, SO I MADE ONE WITH MATH."
LOGARITHMIC
"LOOK, IT'S TAPERING OFF!"
EXPONENTIAL
"LOOK, IT'S GROWING UNCONTROLLABLY!"
LOESS
"I'M SOPHISTICATED, NOT LIKE THOSE BUMBLING POLYNOMIAL PEOPLE."
LINEAR, NO SLOPE
"I'M MAKING A SCATTER PLOT BUT I DON'T WANT TO."
LOGISTIC
"I NEED TO CONNECT THESE TWO LINES, BUT MY FIRST IDEA DIDN'T HAVE ENOUGH MATH."
CONFIDENCE INTERVAL
"LISTEN, SCIENCE IS HARD. BUT I'M A SERIOUS PERSON DOING MY BEST."
PIECEWISE
"I HAVE A THEORY, AND THIS IS THE ONLY DATA I COULD FIND."
CONNECTING LINES
"I CLICKED 'SMOOTH LINES' IN EXCEL."
AD-HOC FILTER
"I HAD AN IDEA FOR HOW TO CLEAN UP THE DATA. WHAT DO YOU THINK?"
HOUSE OF CARDS
"AS YOU CAN SEE, THIS MODEL SMOOTHLY FITS THE- WAIT NO NO DON'T EXTEND IT AAAAAA!!"

Regression

- OLS

$$\sum_{i=1}^{M}(y_i - \hat{y}_i)^2 = \sum_{i=1}^{M}\left(y_i - \sum_{j=0}^{p} w_j \times x_{ij}\right)^2$$

- Ridge

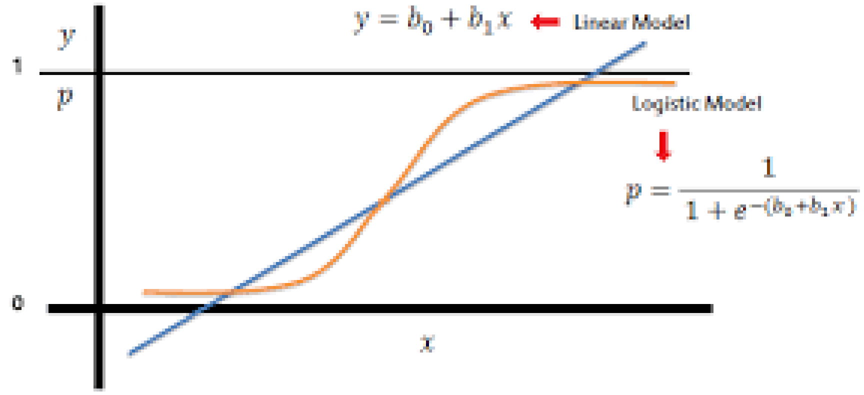
$$\sum_{i=1}^{M}(y_i - \hat{y}_i)^2 = \sum_{i=1}^{M}\left(y_i - \sum_{j=0}^{p} w_j \times x_{ij}\right)^2 + \lambda \sum_{j=0}^{p} w_j^2$$

- Lasso

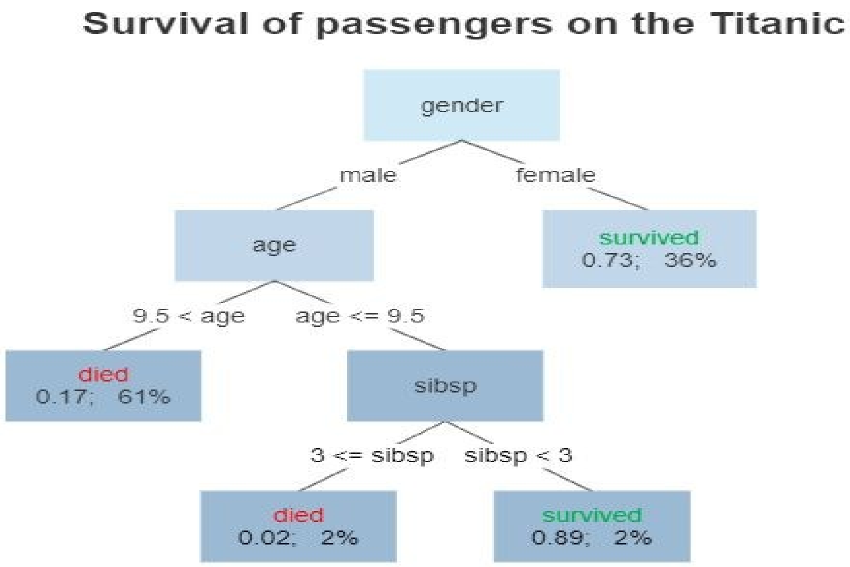
$$\sum_{i=1}^{M}(y_i - \hat{y}_i)^2 = \sum_{i=1}^{M}\left(y_i - \sum_{j=0}^{p} w_j \times x_{ij}\right)^2 + \lambda \sum_{j=0}^{p} |w_j|$$

Logistics Regression

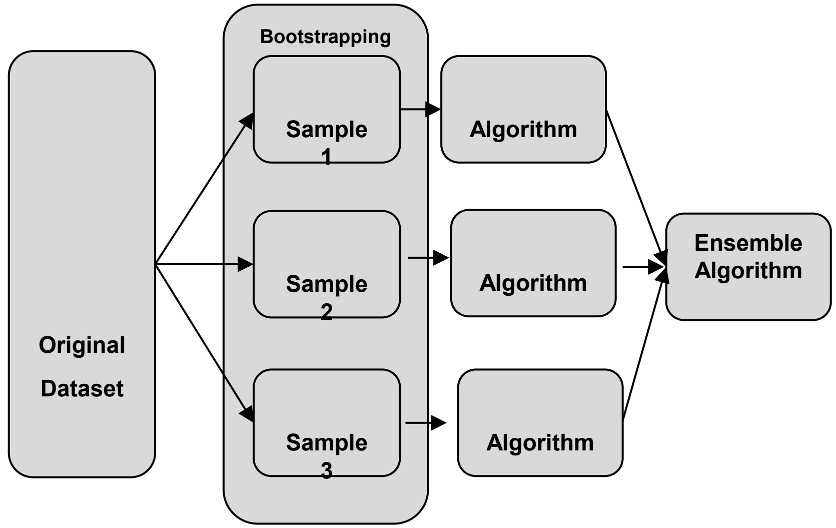
- Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable, although many more complex extensions exist



Decision Tree

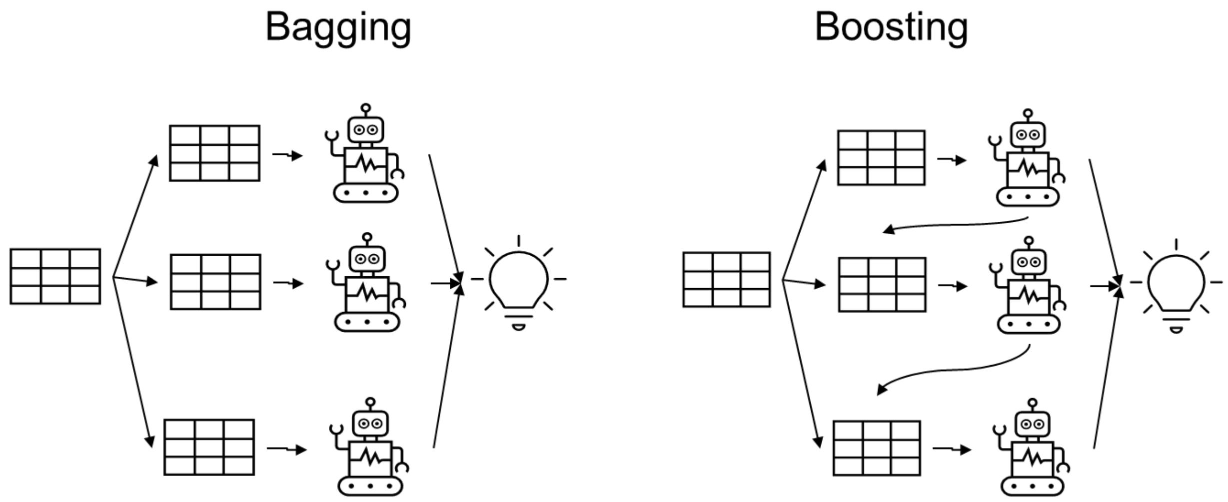


- Classification or Regression
- breaks down a data set into smaller and smaller subsets
- final result is a tree with decision nodes and leaf nodes.



Ensemble

- a Machine Learning concept in which the idea is to train multiple models using the same learning algorithm.
- classification, regression and other tasks
- multitude of decision trees at training time
- outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees

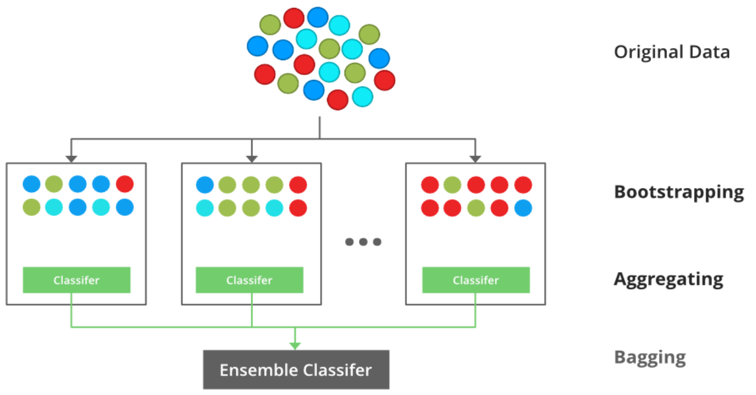


Bagging vs. Boosting

- classification, regression and other tasks
- multitude of decision trees at training time
- outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

Bagging

- create multiple bootstrap samples
- fit a weak learner
- aggregate -> “average” their
- outputs is an ensemble model with less variance that its components.

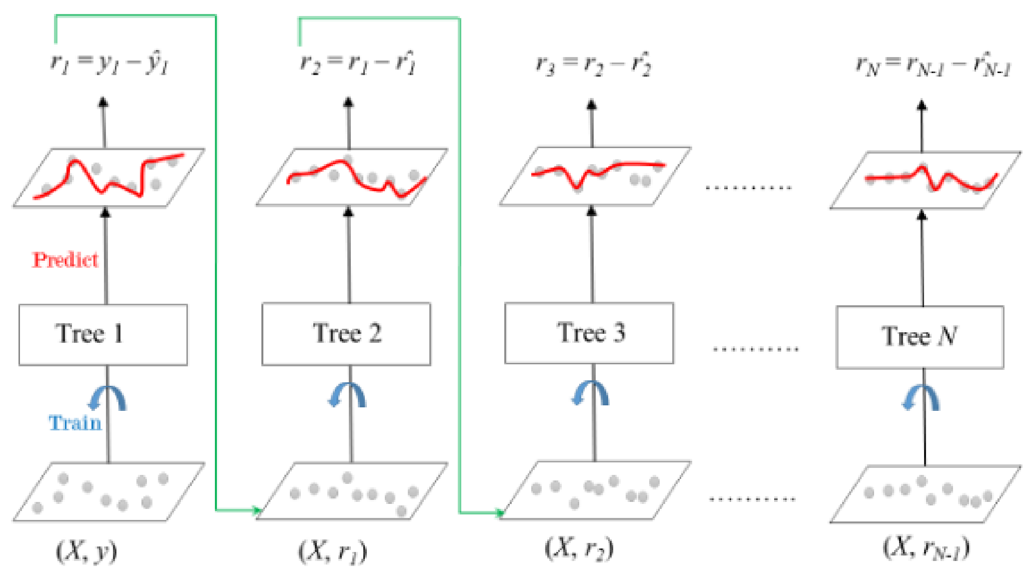


$$s_L(.) = \frac{1}{L}\sum_{l=1}^{L} w_l(.) \qquad \text{(simple average, for regression problem)}$$

$$s_L(.) = \arg\max_k [card(l|w_l(.) = k)] \qquad \text{(simple majority vote, for classification problem)}$$

Boosting

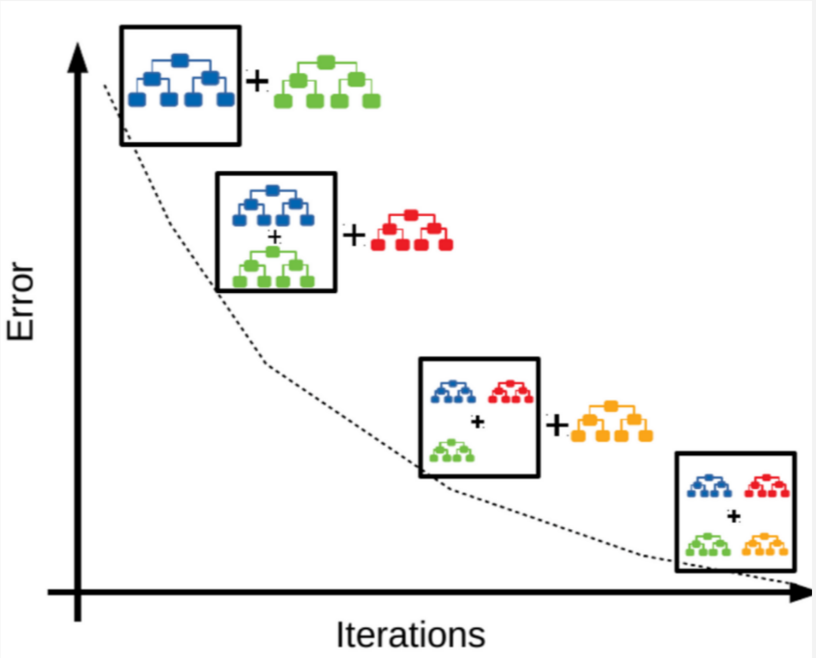
- in fitting sequentially multiple weak learners in a very adaptative way
- each new model focus its efforts on the most difficult observations to fit up to now
- at the end of the process, is obtained a strong learner with lower bias
- Boosting can also have the effect of reducing variance



$$(c_l, w_l(.)) = \underset{c,w(.)}{\arg\min} E(s_{l-1}(.) + c \times w(.)) = \underset{c,w(.)}{\arg\min} \sum_{n=1}^{N} e(y_n, s_{l-1}(x_n) + c \times w(x_n))$$

Gradient boosting

- type of machine learning boosting
- relies on the assumption that the best possible next model, when combined with previous models, minimizes the overall prediction error
- key idea: set the target outcomes for this next model to minimize the error



Gradient Boosting Algorithm

1. Initialize model with a constant value:

$$F_0(x) = \underset{\gamma}{argmin} \sum_{i=1}^{n} L(y_i, \gamma)$$

2. for $m = 1$ to M:

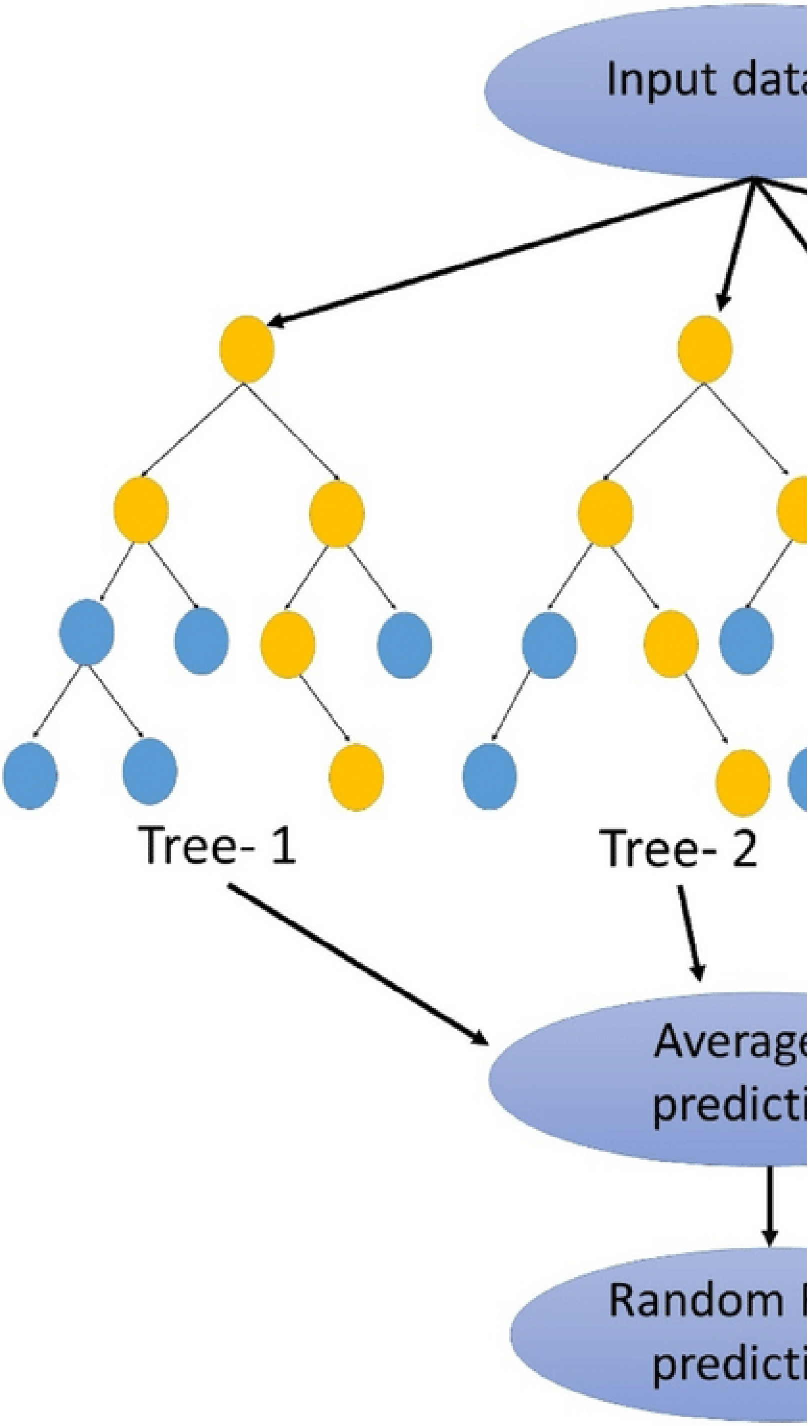
   2-1. Compute residuals $r_{im} = -\left[\frac{\partial L(y_i,\ F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)}$ $for\ i = 1,\dots,n$

   2-2. Train regression tree with features x against r and create terminal node reasions R_{jm} for $j = 1,\dots,J_m$

   2-3. Compute $\gamma_{jm} = \underset{\gamma}{argmin} \sum_{x_i \in R_{jm}} L(y_i, F_{m-1}(x_i) + \gamma)$ $for\ j = 1,\dots,J_m$

   2-4. Update the model:

$$F_m(x) = F_{m-1}(x) + \nu \sum_{j=1}^{J_m} \gamma_{jm} 1(x \in R_{jm})$$



Random Forest

- is a bagging method where deep trees, fitted on bootstrap samples, are combined to produce an output with lower variance
- classification, regression and other tasks
- multitude of decision trees at training time
- outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

Differences Between Bagging and Boosting

S.NO	Bagging	Boosting
1.	The simplest way of combining predictions that belong to the same type.	A way of combining predictions that belong to the different types.
2.	Aim to decrease variance, not bias.	Aim to decrease bias, not variance.
3.	Each model receives equal weight.	Models are weighted according to their performance.
4.	Each model is built independently.	New models are influenced by the performance of previously built models.
5.	Different training data subsets are randomly drawn with replacement from the entire training dataset.	Every new subset contains the elements that were misclassified by previous models.
6.	Bagging tries to solve the over-fitting problem.	Boosting tries to reduce bias.
7.	If the classifier is unstable (high variance), then apply bagging.	If the classifier is stable and simple (high bias) the apply boosting.
8.	Example: The Random Forest model uses Bagging.	Example: The AdaBoost uses Boosting techniques

Bagging vs. Boosting

Python Libraries

scikit learn

statsmodels